Cricket Ball Prediction Model V2:
Unified Heterogeneous Graph Architecture

Architecture Documentation

December 18, 2025

Abstract

This document describes Version 2 of the cricket ball prediction model. The model represents **all information as a single heterogeneous graph** where different types of nodes (venue, players, match state, ball history) are connected by typed edges that encode cricket-specific relationships. This enables processing full innings history while maintaining computational efficiency through sparse, structured attention patterns.

Contents

1 Overview: What is a Heterogeneous Graph?

1.1 The Key Idea

A **heterogeneous graph** contains multiple types of nodes and multiple types of edges. Unlike a standard graph where all nodes are the same, our cricket graph has:

- **Different node types**: venue, teams, players, match state, momentum, ball history
- **Different edge types**: "conditions", "matchup", "precedes", "same_bowler", etc.

Each edge type can have its own neural network (convolution operator), allowing the model to learn relationship-specific patterns.

1.2 Why This Matters for Cricket

Cricket prediction requires understanding many different types of information and their relationships:

- **Who** is batting and bowling (player identities)
- **Where** the match is being played (venue characteristics)
- **What** is the current score, required rate, wickets in hand
- **How** the players are performing today (runs, strike rate, economy)
- **What happened** in previous balls (ball-by-ball history)

By encoding all of this in a single graph, the model can learn complex interactions (e.g., "Rohit struggles against left-arm spin at the MCG in the death overs").

2 Node Types: The Building Blocks

The graph contains **21 context nodes** organized into **6 categories**, plus N ball history nodes.

Important distinction:

- A **category** is a semantic grouping (e.g., "Actor" = all player-related nodes)
- Individual **nodes** within a category represent specific pieces of information

2.1 Category 1: Global (3 nodes)

These nodes represent match-level constants that don't change during the innings:

Node Name	Features	What it Represents
`venue`	32-dim embedding	The ground (MCG, Eden Gardens, etc.). Learned embedding captures pitch behavior, boundaries, historical scoring patterns.
`batting_team`	32-dim embedding	The team currently batting. Captures team-level tendencies.
`bowling_team`	32-dim embedding	The team currently bowling.

Table 1: Global category: 3 nodes representing match constants

Example: At the MCG, India batting vs Australia bowling → venue, batting_team, bowling_team nodes initialized with their learned embeddings.

2.2 Category 2: State (5 nodes)

These nodes capture the current match situation. They change as the match progresses:

Node Name	Features	What it Represents
`score_state`	4 features	Current score, wickets, balls, innings
`chase_state`	3 features	Target, required rate, is_chase (2nd innings only)
`phase_state`	5 features	Powerplay/middle/death phase, over progress, **is_first_ball** cold-start indicator
`time_pressure`	3 features	Balls remaining, urgency, is_final_over
`wicket_buffer`	2 features	Wickets in hand, is_tail indicator

Table 2: State category: 5 nodes representing current match situation

Example: Score 150/3 in 15 overs chasing 180 → score_state=(150, 3, 10.0), chase_state=(180, 6.0, 30), phase_state=(0, 1, 0, 0.75, 0).

Note: `is_first_ball` in phase_state is a cold-start indicator (1.0 if this is the very first ball of the innings, 0.0 otherwise).

2.3 Category 3: Actor (7 nodes)

These nodes represent the current players on the field and their performance:

Node Name	Features	What it Represents
`striker_identity`	Hierarchical embedding	WHO is on strike (player→team→role fallback for unknown players)
`striker_state`	8 features	HOW they're batting: runs, balls, SR, dot%, boundaries, set indicator, **is_debut_ball**, **balls_since_on_strike**
`nonstriker_identity`	Hierarchical embedding	WHO is at the non-striker's end (with cold-start fallback)
`nonstriker_state`	7 features	HOW the non-striker has been batting (includes is_debut_ball)
`bowler_identity`	Hierarchical embedding	WHO is bowling (with cold-start fallback)
`bowler_state`	6 features	HOW they're bowling: overs, runs, wickets, economy, dot%
`partnership`	4 features	Partnership runs, balls, run rate, boundaries

Table 3: Actor category: 7 nodes representing current players

Key insight: Separating identity from state allows the model to learn "Bumrah is generally accurate" (identity) independently from "Bumrah is bowling well today" (state).

Note: `is_debut_ball` in striker/nonstriker state is 1.0 if this is the player's first ball of the match (cold-start handling).

Note: `balls_since_on_strike` in striker_state captures the "cold restart" effect: 0.0 if the striker faced the previous ball, increasing toward 1.0 if they've been at non-striker end for 12+ balls (2 overs). This helps the model understand that a batsman coming back on strike after a period at non-striker is less "in rhythm" than one continuously facing.

2.4 Category 4: Dynamics (4 nodes)

These nodes capture recent momentum and pressure patterns:

Node Name	Features	What it Represents
`batting_momentum`	4 features	Recent scoring rate, boundary%, acceleration
`bowling_momentum`	4 features	Recent economy, dot%, control
`pressure`	3 features	Required rate vs actual rate, mounting pressure
`dot_pressure`	3 features	Consecutive dots, dot ball spiral indicator

Table 4: Dynamics category: 4 nodes representing momentum and pressure

Why this matters: Cricket outcomes are heavily influenced by momentum. A batsman who just hit two boundaries is in a different mental state than one who faced 5 dots.

2.5 Category 5: Ball (N nodes)

Each historical ball in the innings becomes a node:

Features	Description
17 numeric features	runs, is_wicket, over, ball_in_over, is_boundary, extras (wide, noball, bye, legbye), wicket types (bowled, caught, lbw, run_out, stumped, other), **striker_run_out**, **nonstriker_run_out**
64-dim bowler ID	Embedding of who bowled this ball
64-dim batsman ID	Embedding of who faced this ball

Table 5: Ball nodes: one per historical delivery (now with run-out attribution)

Run-out attribution: The striker_run_out and nonstriker_run_out features disambiguate WHO was run out, enabling better risk assessment.

Total per ball: $17 + 64 + 64 = 145$ features $\rightarrow$ projected to 128-dim.

2.6 Category 6: Query (1 node)

A special node used to aggregate all information for the final prediction:

- Initialized with zeros
- After message passing, contains aggregated information from the entire graph
- Final prediction is made from this node's representation

2.7 Summary: Total Node Count

Category	Nodes in Category	Role
Global	3	Match constants
State	5	Current situation
Actor	7	Players on field
Dynamics	4	Momentum/pressure
Ball	N (variable)	Full innings history
Query	1	Prediction aggregation
Total	**20 + N**	

Table 6: Node count by category

3 Edge Types: The Relationships

Edges encode **how nodes relate to each other**. Different edge types have different meanings and use different neural network operations.

3.1 Understanding Edge Type Notation

An edge type is written as: `(source_type, relation, target_type)`

For example: `(global, conditions, state)` means "global nodes have a 'conditions' relationship with state nodes".

Important: The categories (global, state, etc.) contain multiple nodes. An edge type like `(global, conditions, state)` means edges connect nodes *within* those categories.

3.2 Category 1: Hierarchical Edges (3 types)

These edges encode a **top-down conditioning** structure: higher-level context influences lower-level interpretation.

Edge Type	Connectivity	Meaning
`(global, conditions, state)`	$3 \to 5$ (15 edges)	Venue/teams influence how we interpret the score
`(state, conditions, actor)`	$5 \to 7$ (35 edges)	Match situation influences how we interpret player performance
`(actor, conditions, dynamics)`	$7 \to 4$ (28 edges)	Current players influence how we interpret momentum

Table 7: Hierarchical edges: top-down conditioning

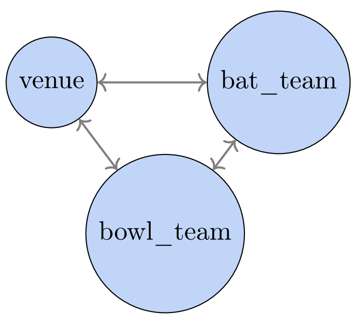
Concrete example: 150/3 means different things at the MCG (good) vs Chennai (average). The edge from `venue` to `score_state` allows this contextual interpretation.

3.3 Category 2: Intra-Layer Edges (4 types)

These edges connect nodes **within the same category**, allowing related information to interact.

3.3.1 What does "global $\leftrightarrow$ global" mean?

This means edges between the 3 nodes in the global category:



6 edges total (bidirectional)
"venue $\leftrightarrow$ bat_team", "venue $\leftrightarrow$ bowl_team", "bat_team $\leftrightarrow$ bowl_team"

Figure 1: Intra-layer edges within the Global category

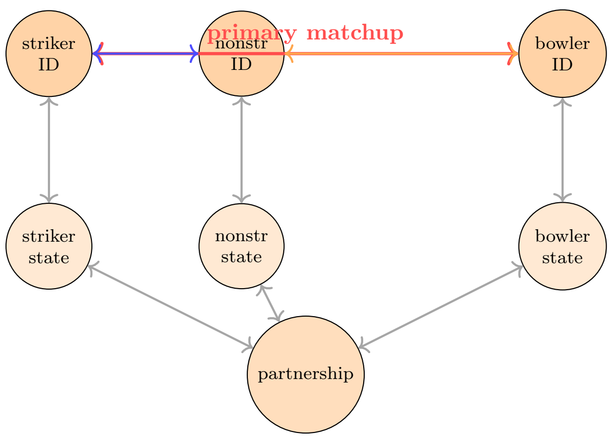
Why it matters: India playing at home vs Australia playing away is different from the reverse. The venue-team combination matters.

Edge Type	Edges	What it Captures
`(global, relates_to, global)`	6	Home/away advantage, venue-team combinations
`(state, relates_to, state)`	20	Score relates to required rate, phase relates to pressure
`(actor, matchup, actor)`	22	Striker-bowler confrontation, partnership dynamics
`(dynamics, relates_to, dynamics)`	12	Batting momentum vs bowling momentum (zero-sum)

Table 8: Intra-layer edges: within-category relationships

3.3.2 The Actor Matchup Graph

The `(actor, matchup, actor)` edges deserve special attention. They encode:



Red: Striker vs Bowler (the key prediction)
Orange: Non-striker vs Bowler (run-out risk)
Blue: Striker ↔ Non-striker (partnership chemistry)

Figure 2: Actor matchup edges capture player interactions

3.4 Category 3: Temporal Edges (6 types)

These edges encode the **structure of ball-by-ball history**. This is where V2 gains efficiency over transformer attention.

3.4.1 Multi-Scale Temporal Architecture

Cricket patterns occur at different time scales:

- **Within-over (1-6 balls):** Immediate pressure, bowler's current plan
- **2-over window (7-18 balls):** Momentum shifts, scoring patterns
- **Historical (19+ balls):** Phase patterns, earlier wickets' impact

We use **three separate edge types** for these scales:

Edge Type	Connects	Neural Network
`recent_precedes`	Balls within 6 deliveries	TransformerConv (fast decay, attention to recency)
`medium_precedes`	Balls 7-18 apart	TransformerConv (medium decay)
`distant_precedes`	Balls 19+ apart (sparse)	SAGEConv (simple mean, sparse connections)

Table 9: Multi-scale temporal edges

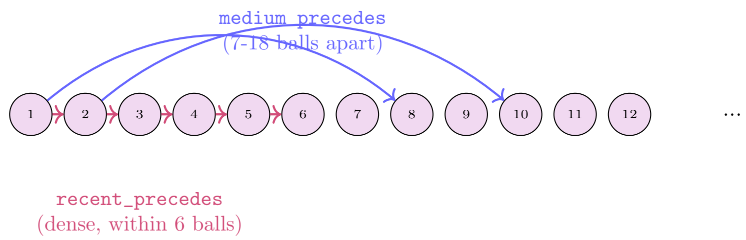


Figure 3: Multi-scale temporal edges (distant not shown for clarity)

3.4.2 Same-Bowler and Same-Batsman Edges (with Temporal Decay)

These edges connect balls by the same player, with **temporal decay edge attributes**:

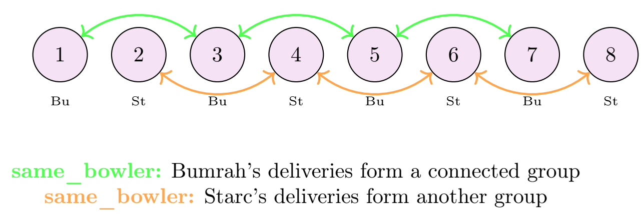


Figure 4: same_bowler edges group a bowler's spell

Temporal decay edge attributes:

- `same_bowler`: 1.0 – (ball_distance/24.0) (4-over spell window)
- `same_batsman`: 1.0 – (ball_distance/60.0) (10-over innings window)

Recent balls matter more than distant ones. The model uses `TransformerConv` with `edge_dim=1` to learn attention patterns that respect this decay.

Why this matters: The model can ask "How has Bumrah been bowling *recently*?" by looking at his deliveries with recency weighting, without needing to attend equally to all balls.

3.4.3 Same-Over Edges (CAUSAL)

`same_over` connects balls within the same over. This captures within-over context:

- Same bowler rhythm and plan for the over
- Field placement context
- Batsman reading the bowler

Critical: Like same_matchup, same_over edges are **CAUSAL (older → newer only)** to prevent train-test distribution shift.

3.4.4 Same-Matchup Edges (CAUSAL)

`same_matchup` connects balls with the same bowler-batsman combination:

Critical: Both same_over and same_matchup edges are **UNIDIRECTIONAL (older → newer)**. This prevents "future information leakage":

- During training, the graph contains future balls
- Bidirectional edges would let the model "see" future outcomes
- At inference time, only historical balls exist
- Causal edges ensure the model learns patterns valid at inference

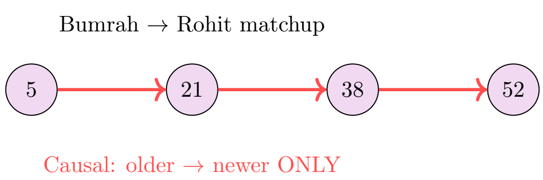


Figure 5: same_matchup edges are causal to prevent distribution shift

3.5 Category 4: Cross-Domain Edges (4 types)

These edges connect ball history to current context nodes:

Edge Type	Meaning	Connectivity
`(ball, faced_by, striker_identity)`	Balls faced by current striker	Variable
`(ball, bowled_by, bowler_identity)`	Balls bowled by current bowler	Variable
`(ball, partnered_by, nonstriker_identity)`	Balls involving current non-striker	Variable
`(ball, informs, dynamics)`	Recent balls inform momentum	12 → 4

Table 10: Cross-domain edges connect history to context

Critical: Correct Player Attribution

Cross-domain edges ONLY connect to balls involving the CURRENT players:

- If Kohli faced balls 1-20 then got out, and Sharma is now batting
- Balls 1-20 do NOT connect to `striker_identity` (which is now Sharma)
- Only balls Sharma actually faced will connect

This respects the Z2 symmetry of striker/non-striker swapping.

3.6 Category 5: Query Edges (2 types)

3.6.1 Attends Edges

The query node receives information from all other nodes:

Edge Type	Connectivity
`(*, attends, query)`	All 20 context nodes + N balls → query

3.6.2 Drives Edges (NEW)

Dynamics nodes **directly drive** prediction through feedback loops:

Edge Type	Meaning
`(dynamics, drives, query)`	Momentum and pressure directly influence prediction

Why a separate edge type?
The `drives` edges capture **causal feedback loops**:

1. **Confidence Spiral:** High batting momentum → more aggressive shots → more runs → higher momentum
2. **Required Rate Pressure:** High pressure → risk-taking → boundaries OR wickets
3. **Dot Ball Spiral:** High dot pressure → desperate shots → wickets → rebuilding

By having learned attention weights on `drives` edges, the model can weight different dynamics signals appropriately.

3.7 Edge Type Summary

Category	Edge Types	Purpose
Hierarchical	3	Top-down context conditioning
Intra-layer	4	Within-category interactions
Temporal	7	Ball history (multi-scale + actor grouping + **same_over**)
Cross-domain	4	Connect history to context
Query	2	Prediction aggregation + dynamics drive
Total	**20**	

Table 11: 20 edge types organized by purpose (now includes same_over edges)

4 Full Graph Visualization

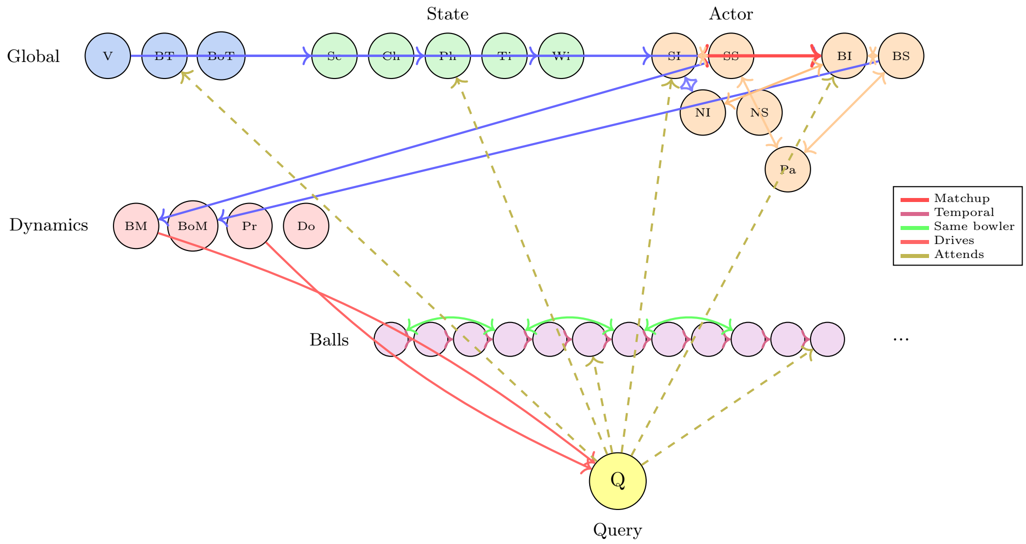


Figure 6: Complete unified graph structure

5 Model Architecture

5.1 Three-Stage Pipeline

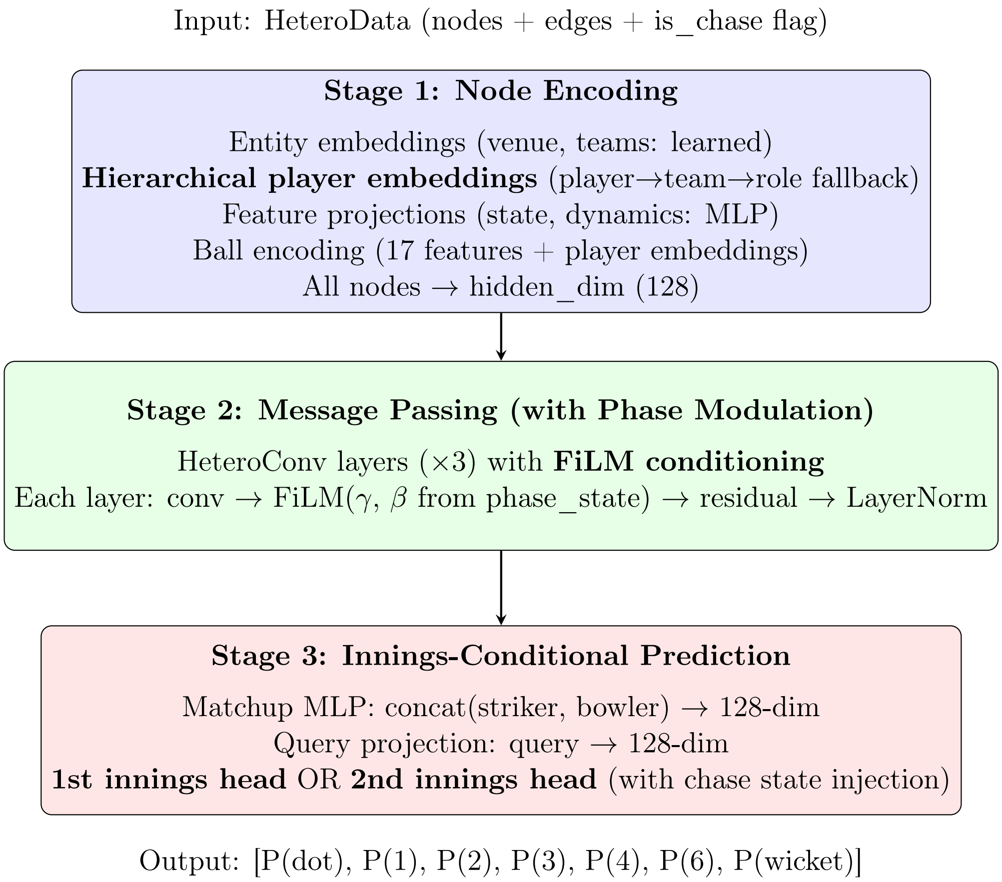


Figure 7: Three-stage model pipeline with FiLM modulation and innings-conditional heads

5.2 Hybrid Readout: Why?

Cricket ball prediction is fundamentally an **edge-level task**: the outcome depends on the specific striker-bowler matchup, modulated by context.

The hybrid readout combines:

1. **Matchup interaction:** Direct combination of striker and bowler representations after message passing

2. **Query aggregation:** Global context (venue, phase, momentum) aggregated by the query node

This respects the geometric structure: prediction is at the matchup level, influenced by graph-level context.

5.3 Convolution Choices per Edge Type

Edge Type	Convolution	Rationale
Hierarchical (conditions)	GATv2Conv	Learn which context matters
Intra-layer (relates_to)	GATv2Conv	Self-attention for interactions
Actor matchup	GATv2Conv	Learn matchup dynamics
recent/medium_precedes	TransformerConv	Edge features for temporal distance
distant_precedes	SAGEConv	Simple mean for sparse history
same_bowler/batsman	**TransformerConv**	**Temporal decay edge features (4/10-over)**
same_matchup (causal)	GATv2Conv	Historical matchup outcomes
same_over (CAUSAL)	**GATv2Conv**	**Within-over context (older→newer only)**
Cross-domain (faced/bowled/partnered)	GATv2Conv	Attention-weighted recency
Dynamics (informs)	SAGEConv	Simple aggregation
Dynamics (drives)	GATv2Conv	Weight momentum vs pressure
Query (attends)	GATv2Conv	Learn what matters for prediction

Table 12: Edge-type-specific convolution operators (updated with temporal decay and same_over)

6 Training: Focal Loss for Class Imbalance

Cricket outcomes are heavily imbalanced:

- Dots: $\sim$35-40%
- Singles: $\sim$25-30%
- Twos: $\sim$5-8%
- Threes: $\sim$1-2%
- Fours: $\sim$12-15%
- Sixes: $\sim$5-8%
- Wickets: $\sim$5%

Standard cross-entropy loss is dominated by the majority class (dots). We use **Focal Loss**:

$$\mathcal{L}_{focal} = -\alpha_t(1 - p_t)^\gamma \log(p_t)$$

where:

- p_t = model's probability for the correct class
- $\gamma = 2.0$ = focusing parameter (higher = more focus on hard examples)
- α_t = optional class weights

Key insight: $(1 - p_t)^\gamma$ down-weights "easy" examples where the model is already confident, focusing learning on hard/rare cases like wickets.

6.1 Training Configuration

Parameter	Value
Hidden dimension	128
Number of layers	3
Attention heads	4
Dropout	0.1
Loss	Focal Loss ($\gamma = 2.0$)
Optimizer	AdamW (lr=1e-3, wd=0.01)
Scheduler	Cosine annealing
Early stopping	Patience 10 epochs
Estimated parameters	$\sim$720K

Table 13: Model and training configuration

7 Why Full History Now Works

7.1 The Quadratic Problem (V1)

In V1's Transformer, every ball attends to every other ball:

$$\text{Attention pairs} = \frac{n(n-1)}{2} = O(n^2)$$

History Length	Attention Pairs
24 balls	276
60 balls	1,770
120 balls (full innings)	7,140

Table 14: Quadratic growth in V1

7.2 The Sparse Solution (V2)

In V2, attention only flows along explicit edges. Cricket structure provides natural sparsity:

- Only ∼6 bowlers per innings → sparse same_bowler
- Only ∼4-6 batsmen → sparse same_batsman
- Matchups are intersection of above → very sparse
- Multi-scale temporal limits long-range connections

History Length	V1 Attention	V2 Edges	Speedup
24 balls	576	∼150	4x
60 balls	3,600	∼800	4.5x
120 balls (full innings)	14,400	∼2,500	**6x**

Table 15: Computational comparison: V1 vs V2

Key insight: V2 is not just faster—it's more informative. The 20 context nodes (venue, players, dynamics) provide rich structure that V1 processed separately.

8 Interpretability Benefits

The unified graph provides natural interpretability:

1. **Edge attention weights**: Which historical balls mattered most?
2. **Same-bowler attention**: How much did the bowler's spell inform the prediction?
3. **Matchup attention**: How important was the striker-bowler confrontation?
4. **Dynamics drives attention**: Was momentum or pressure more influential?
5. **Hierarchical attention**: Did venue or match state dominate?

All of these are directly extractable from the GATv2Conv attention weights.

9 Summary

The V2 architecture represents cricket prediction as a heterogeneous graph where:

- **21 context nodes** capture venue, teams, match state, players, and dynamics
- **N ball nodes** capture full innings history (17 features including run-out attribution)
- **20 edge types** encode cricket-specific relationships (now includes same_over)
- **Multi-scale temporal edges** capture patterns at different time scales
- **Temporal decay edge attributes** for same_bowler (4-over) and same_batsman (10-over)
- **Causal same_over edges** capture within-over context (bowler plans, batsman reading)
- **Causal same_matchup edges** prevent train-test distribution shift
- **balls_since_on_strike** feature captures striker "cold restart" after non-striker period
- **Hierarchical player embeddings** handle cold-start (unknown players)
- **FiLM phase modulation** enables phase-conditional message passing
- **Innings-conditional prediction heads** separate 1st/2nd innings logic
- **Hybrid readout** combines matchup interaction with global context
- **Focal loss** handles class imbalance

This design follows Geometric Deep Learning principles: the inductive bias matches cricket's inherent structure, enabling efficient processing of full innings while respecting symmetries (player attribution, temporal causality, phase dynamics).